



Assessing responses of hydrological processes to climate change over the southeastern Tibetan Plateau based on resampling of future climate scenarios

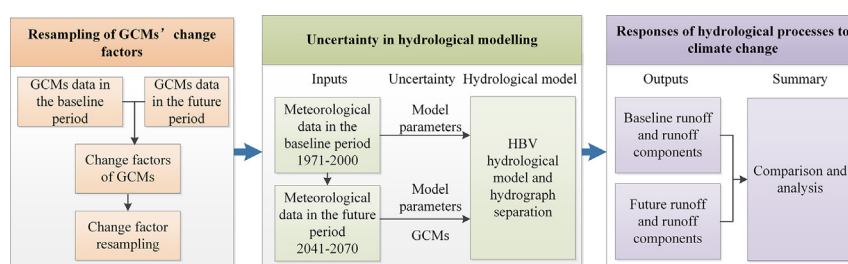
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HIGHLIGHTS

- The LHS method can well resample change factors to reflect GCMs' uncertainty.
- Future precipitation, temperature and total runoff probably increase in UYZR and ULR.
- More rainfall-induced runoff and less snowmelt-induced runoff possibly occur in both basins.
- Hydrological regimes are different between UYZR and ULR.

GRAPHICAL ABSTRACT



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ABSTRACT

With global warming, hydrological regimes in the headwater basins of the Tibetan Plateau (TP) have significantly changed. Investigating the responses of hydrological processes to climate change in TP has become more and more important to make robust strategies for water resources management. However, using just a few GCMs may constrain the uncertainty in assessment of climate impacts. Therefore, a framework is proposed in this study to generate ensemble climate change scenarios and then investigate changes of hydrological processes under climate change in the upper reaches of Yarlung Zangbo River basin (UYZR) and Lancang River basin (ULR). Firstly, the Latin Hypercube Simulation (LHS) is used to generate an ensemble of future climate change scenarios by resampling change factors of meteorological variables from 18 GCMs under emission scenarios RCP2.6 and RCP8.5. The inherent dependence structures of change factors, i.e. the correlations of change factors among 12 months for different meteorological variables, are also considered in ensembles. Secondly, the HBV hydrological model coupled with a degree-day snowmelt model is applied to explore the potential change of runoff in the future period 2041–2070. Results show that: 1) the resampling method is effective and can provide a wide ensemble of climate change scenarios. 2) Precipitation, temperature and potential evapotranspiration in the UYZR and ULR basins are expected to increase under the two scenarios, particularly under RCP8.5. 3) The total runoff also shows a moderately upward trend in two basins, both mainly due to increased precipitation. In the UYZR basin, fast runoff accounts for a larger proportion in total runoff than slow runoff, while in ULR, both almost play the same role in total runoff. Furthermore, snowmelt-induced runoff in both basins would be less and rainfall-induced runoff will probably become more important in the future.

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1. Introduction

The Tibetan Plateau (TP), famous as the “Asian Water Tower” (Immerzeel et al., 2010) and the “Roof of the World” (Chen et al.,

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2013), is the source of many Asia's large rivers (Indus, Ganges, Brahmaputra, Yangtze, Yellow and Mekong) (Kuang and Jiao, 2016), providing abundant water resources for lives of hundreds of millions of people living downstream (Zhang et al., 2013b). Due to TP's special topographical, geological and climate features, vast areas of glaciers, snow, seasonal frozen ground and even permafrost are distributed over TP (Cuo et al., 2014), resulting in its complex hydrological regimes and high sensitivity to climate change (Wang et al., 2005; Yao et al., 2012). Many previous studies have reported that obvious climate changes have occurred in TP with a warming trend of 0.16–0.36 °C/decade in recent decades (Wang et al., 2008; Wu et al., 2007; Xu et al., 2008). With the warming climate, TP's hydrological dynamics and processes have correspondingly changed in terms of snow melt, glacier retreat and water resources variation (Ji and Kang, 2013; Kang et al., 2010; Piao et al., 2010), and these changes are expected to be enhanced under future continuous warming (Immerzeel et al., 2013; Su et al., 2016). Therefore, quantifying the potential changes of water resources under changing climate environments is important for water managers and policy-makers to develop sustainable water resources strategies over this region.

Many studies have investigated the impacts of climate change on future water resources over TP and most of them found an increasing trend in the total runoff and extreme runoff in this area (Li et al., 2013b; Sperna Weiland et al., 2012a), which are beneficial for social and economic development and downstream water use, but may also lead to natural disasters, such as floods (Yang et al., 2018; Zhang et al., 2017; Zhang et al., 2012). To better understand the hydrological regimes of TP's rivers and figure out the reasons that cause these changes, runoff components separation has become more and more important in recent year (Immerzeel et al., 2013; Immerzeel et al., 2010; Lutz et al., 2014; Su et al., 2016; Zhang et al., 2013b). Generally, there are two methods to achieve hydrograph separation: Isotope Hydrograph Separation (IHS) (Klaus and McDonnell, 2013; Xing et al., 2015) and hydrological modelling (Han et al., 2015; Li et al., 2017; Siderius et al., 2013). Sun et al. (2016) applied the IHS method to successfully analyze the contribution of baseflow, snowmelt water and precipitation to runoff in the Aksu river, the main tributary of the Tarim river in China, and Xing et al. (2015) also determined the relative importance of ice/snow melt, precipitation and baseflow through monitoring the path of stable water isotopes ($\delta^{18}\text{O}$ and $\delta^2\text{H}$) in the Hailuoguo catchment in southwest China. Although the IHS method provides a relatively objective approach to conduct hydrograph separation, it is time-consuming and difficult to operate (Ala-aho et al., 2017), and is also hard to be applied to analyze the runoff components in the future period. By contrast, hydrological modelling is relatively simple and can be flexibly applied to various temporal and spatial scales, particularly for investigating the future changes of runoff compositions. Siderius et al. (2013) and Xing et al. (2015) used a ratio of rainfall and melt water to obtain runoff components from hydrological model simulation.

To achieve the impact assessment of climate change on runoff, Global Climate Models (GCMs) are generally the primary available tools (Hoang et al., 2016; Immerzeel et al., 2012; Sillmann et al., 2013). However, GCMs have been commonly acknowledged as the largest source of uncertainty in impact studies (Chen et al., 2011; Kay et al., 2008; Vetter et al., 2016). To consider the uncertainty of GCMs, the common practice is to use multiple GCMs to provide an ensemble of future projections (Chiew et al., 2009; Sperna Weiland et al., 2012b; Wu et al., 2018). For example, Li et al. (2013b) utilized 20 GCMs to simulate the future projected runoff in the southeastern TP and Wu et al. (2018) analyzed the runoff response to climate change for China's 14 large rivers using 28 GCMs. In recent years, some studies have pointed out that the uncertainty cannot be adequately explored through only a few GCMs realizations and thus they have begun trying to resample change factors of meteorological variables based on their probability information in order to provide more reliable climate change scenarios (Fatichi et al., 2013; Fatichi et al., 2016; Ledbetter et al., 2011). For instance, Fatichi et al. (2013) utilized the Bayesian methodology to construct the marginal distributions of changes

factors and then used the Monte Carlo technique to resample change factors from their respective marginal distributions. However, up to now the related studies are very limited and most of them rarely considered the inherent dependence structure within change factors. Moreover, change factor resampling has not been further applied in climate assessments.

Apart from using GCMs, hydrological modelling is also an important part in climate change impact analysis, which is responsible to transform meteorological data into runoff (Zhang et al., 2014). However, due to limited understanding in nature and simplifications in representing hydrological processes, all hydrological model structures are in error to some extent (Renard et al., 2010; Tian et al., 2014). Therefore, a chosen hydrological model usually needs to be calibrated using observed data so that a series of parameters can be selected to plausibly represent the actual hydrological processes (Jin et al., 2010). Although different sets of model parameters may finally have the similar hydrological outputs, they may represent different possibilities of hydrological systems. Thus, the uncertainty of model parameters should also be explored like GCMs. Many studies have reported that model parameters are also a large uncertainty source in future runoff modelling (Mirzaei et al., 2015; Zhang et al., 2014). Bastola et al. (2011) found that the uncertainty of hydrological model parameters contributes to almost half of streamflow uncertainty. Zhang et al. (2013a) also pointed out that the uncertainty of model parameters should be taken into consideration for climate change impact analysis as they might have significant impacts on river flows in different hydrological years.

The goal of this study is to fully assess the impacts of climate change on hydrological processes, including runoff and runoff components, in the southeastern TP with simultaneously considering two large uncertainty sources, i.e., GCMs and hydrological model parameters, which can help us better understand hydrological regimes in high mountain regions. Hydrological modelling method is adopted to conduct hydrograph separation. As for GCMs' uncertainty, we propose the Latin hypercube simulation method (LHS) for the first time to resample change factors in this study to fully reflect the uncertainty of GCMs and further apply change factor resampling to climate change impact assessment. Different from the existing method used by Fatichi et al. (2013) that give different weights to different GCMs based on their performances with respect to historical climate, the LHS method treats each GCM equally. Since the Delta method is applied in this study to perturb the historical observations using change factors of GCMs to obtain future meteorological data and its significant advantage is removing the biases between GCMs simulations and observations, each GCM's projected change factor is considered to be irrelevant to GCM's historical performance and represents one possibility of future change. Therefore, each GCM is given equal weight and the LHS method is adopted to resample GCMs' change factors. In addition, the dependence structures of change factors among 12 months within each meteorological variable are remained in the LHS method. Compared with the Monte Carlo method, the LHS method is simpler and can remain the distribution of change factors with fewer samples (Cai et al., 2014; Janssen, 2013). The main contents of this study are (1) to construct a large ensemble of future climate projections by resampling change factors from limited GCMs; and (2) to explore the responses of hydrological processes to climate change over the study area with simultaneously considering the uncertainty of GCMs and model parameters. The rest of this paper is structured as follows: Section 2 presents the study area and data used in this study; Section 3 describes the methodology utilized for resampling change factors and hydrological modelling; Discussion is provided in Section 4 followed by the conclusions in Section 5.

2. Study area and data

2.1. Study area

This study mainly focused on two basins in the southeast of TP, i.e., the upstream of Yarlung Zangbo River basin (UYZR) and Lancang

River basin (ULR) that are respectively controlled by Nuxia hydrological station with a drainage area of approximately 192,900 km² and Changdu hydrological station with approximately 53,700 km² drainage area in China's territory (Fig. 1). The Yarlung Zangbo River, upper reaches of Brahmaputra River, is one of the world's highest rivers with a mean elevation above 4000 m above sea level (Li et al., 2013b), and it is also the longest plateau river in China, stretching 2229 km across the southern Tibet from west to east (Cai et al., 2017). Due to its special location and topographical features, the climate in the UYZR basin is predominantly characterized by the Indian monsoon in summer and westerly system in winter, resulting in about 80% of annual precipitation occurring from May to September and little occurring in winter and spring (often in the form of snow) (Cuo et al., 2014; Lutz et al., 2014). The mean annual precipitation in UYZR is approximately 427 mm, the mean annual air temperature is about 5.92 °C (Li et al., 2013a), and the mean annual potential evapotranspiration (PET) reaches 998 mm during 1971–2000. Approximately 2.1% of the basin is covered by glacier (4225 km²) (Su et al., 2016) and nearly 30% of the area is covered by perennial snow and seasonal snow.

The Lancang River basin is located in the upper of Mekong River, which originates in TP in Qinghai Province. The elevation in the ULR basin ranges from 3213 to 5833 m. The ULR basin is primarily influenced by the East Asian monsoon in summer and westerlies in dry winter with the climate characteristics of intense solar radiation, low temperature and large diurnal temperature difference. Average annual precipitation is around 524 mm during 1971–2000, with about 75% distributed between June and September. In ULR, glacier and snow make up a small proportion of the area (Zhang et al., 2013b) and rainfall is the dominant contributor to runoff (Su et al., 2016).

2.2. Meteorological and hydrological data

Gauged data from 17 meteorological stations and 3 meteorological stations respectively in the UYZR and ULR basins are used, including daily minimum temperature, maximum temperature and daily precipitation from China Meteorological Administration. These stations are shown in Fig. 1. The period of these meteorological data is from 1971 to 2015. Daily streamflow data during the period 1980–2000 are available in the UYZR basin for hydrological model calibration and validation, among which the first year is used as the warming-up period, 1981–1994 as the calibration period and 1995–2000 as the validation period. Compared to the UYZR basin, only short monthly streamflow

data spanning from 2000 to 2014 can be obtained in the ULR basin. Similarly, the first year is utilized for warming up, two-thirds of the data (2001–2010) are for model calibration and the left one-third (2011–2014) are for model validation.

2.3. Climate data

To analyze future changes of hydrological processes, here referring to runoff and runoff components, under climate change in the UYZR and ULR basins, 18 GCMs from the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) are used in this study. The baseline period is 1971–2000 and the future period is 2041–2070. Therefore, monthly climate data of these GCMs for the baseline period and the future period under two scenarios RCP2.6 and RCP8.5, including precipitation, minimum and maximum temperature, are obtained from the World Climate Research Program's (WCRP's) phase 5 of the Coupled Model Intercomparison Project (CMIP5) data sets (<http://cmip-pcmdi.llnl.gov/cmip5/>). The detailed information about the 18 GCMs is listed in Table 1. Climate scenario RCP2.6 represents the lowest emission scenario with radiative forcing peaking at approximately 3 W/m² in 2035 and then reducing to 2.6 W/m² by the end of the 21st century, and RCP8.5 indicates the highest emission scenario in which the increasing radiative forcing reaches 8.5 W/m² by the year 2100 (Sillmann et al., 2013).

3. Methodology

To investigate the responses of hydrological processes to climate change, a general framework is proposed here as shown in Fig. 2. Firstly, change factors of meteorological variables are resampled to provide more ensemble climate change scenarios. Secondly, the HBV model is used to conduct the hydrological modelling for the baseline period and the future period, and hydrograph separation is also conducted. Lastly, the responses of runoff and runoff components to climate change are analyzed. In the following subsections, more detailed information will be given.

3.1. Resampling of change factors

To derive the future projections of runoff and its runoff components in the UYZR and ULR basins, the first work is to obtain the future climate forcing data. The Delta method (Hay et al., 2000; Manning et al., 2009) is

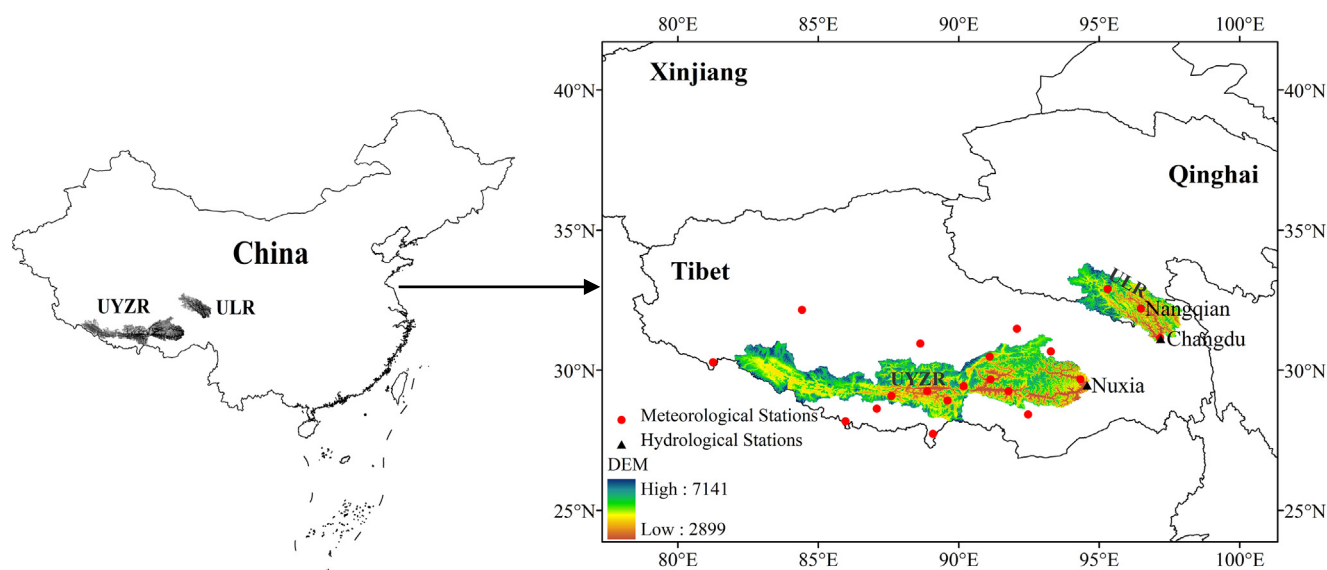


Fig. 1. Location of study area and meteorological stations.

Table 1
Information of 18 selected GCMs.

Code	Model name	Modelling group	Institute ID	Country	Atmosphere resolution (longitude × latitude)
1	BCC-CSM1-1	Beijing Climate Center, China Meteorological Administration	BCC	China	~2.8125° × 2.7906°
2	BNU-ESM	College of Global Change and Earth System Science, Beijing Normal University	GCESS	China	~2.8125° × 2.7906°
3	CanESM2	Canadian Centre for Climate Modelling and Analysis	CCCMA	Canada	~2.8125° × 2.7906°
4	CNRM-CM5	CNRM/Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique	CNRM-CERFACS	France	~1.4060° × 1.4060°
5	CSIRO-Mk3-6-0	CSIRO in collaboration with Queensland Climate Change Centre of Excellence	CSIRO-QCCCE	Australia	~1.8750° × 1.8750°
6	GFDL-CM3	Geophysical Fluid Dynamics Laboratory, National Oceanic and Atmospheric Administration	NOAA GFDL	United States	~2.5000° × 2.0000°
7	GFDL-ESM2G				~2.5000° × 2.0225°
8	GFDL-ESM2M				~2.5000° × 2.0225°
9	GISS-E2-H	Goddard Institute for Space Studies, National Aeronautics and Space Administration	NASA GISS	United States	~2.5000° × 2.0000°
10	GISS-E2-R				
11	HadGEM2-AO	Met Office Hadley Centre	MOHC	United Kingdom	~1.8750° × 1.2500°
12	HadGEM2-ES				
13	IPSL-CM5A-LR	Institute Pierre-Simon Laplace	IPSL	France	~3.7500° × 1.8947°
14	MIROC5	National Institute for Environmental Studies	MIROC	Japan	~1.4063° × 1.4008°
15	MIROC-ESM				~2.8125° × 2.7906°
16	MIROC-ESM-CHEM				~2.8125° × 2.7906°
17	MPI-ESM-LR	Max Planck Institute for Meteorology	MPI-M	Germany	~1.8750° × 1.8653°
18	MRI-CGCM3	Meteorological Research Institute	MRI	Japan	~1.1250° × 1.1215°

adopted in this study for climate projections. The core of the Delta method is using change factors of climate variables projected by GCMs to perturb the historical observation-based forcing data in order to get new forcing data that is representative of the future climate projections

(Birkinshaw et al., 2017). The advantage of the Delta method is that it can effectively remove the discrepancy between GCM outputs and observations by only considering GCMs' relative changes (Su et al., 2016). Based on GCMs monthly average statistics of a historical period

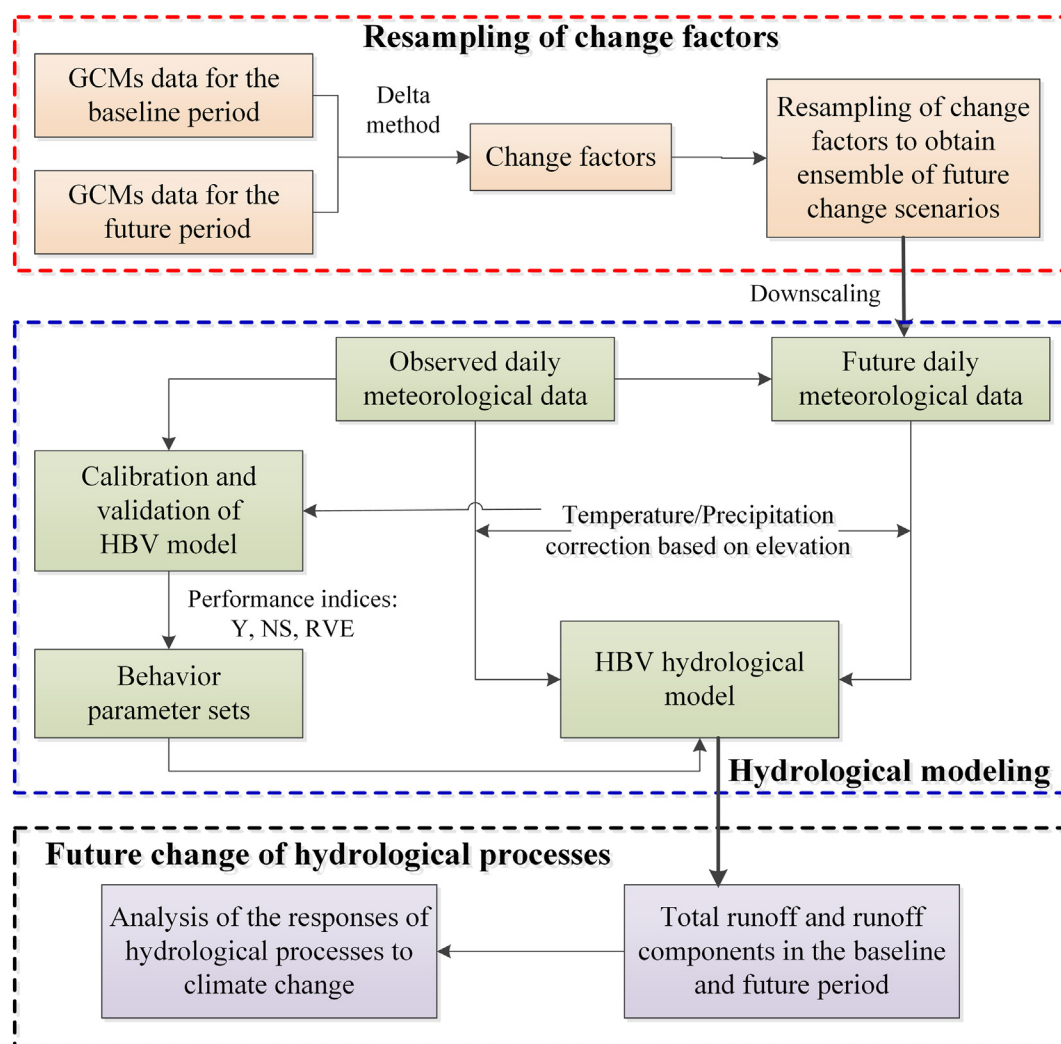


Fig. 2. Framework of this study.

(here 1971–2000) and a future period (here 2041–2070), change factors of climate variables, such as precipitation ($P_{factor} = P_{GCM(2041-2070)}/P_{GCM(1971-2000)}$) and temperatures ($\Delta T = T_{GCM(2041-2070)} - T_{GCM(1971-2000)}$) can be calculated (Anandhi et al., 2011). Change factors from different GCMs represent different climate change scenarios. Since 18 GCMs are selected in this study, only 18 sets of change factors can be obtained under RCP2.6 and RCP8.5, respectively.

Considering the problem that using a few available GCMs would limit the range of climate change scenarios that they can explore, the LHS method (Iman and Conover, 1982) is used in this study to resample change factors of meteorological variables in order to provide more future climate change scenarios. Change factor resampling is to form different combinations of change factors among 12 months for one specified meteorological variable based on its change factors obtained from GCMs. In this method, it is regarded that each GCM model's projected change factor represents one possibility of climate change scenarios. Therefore, each GCM is given an equal weight and we adopt the uniform distribution to resample change factor for each month. Besides, the inherent dependence structures within change factors of different meteorological variables among 12 months are maintained through introducing their rank correlations based on the Cholesky decomposition shown in Fig. 3. The detailed resampling process can refer to Iman and Conover (1982) and Yu et al. (2009).

As for the resampling number N , with N increasing, the multiple combinations of change factors allow one to explore a wider set of possible future scenarios, but the computational time required to take the full advantage of this methodology also grows considerably, which makes it less suitable for subsequent modelling applications (Helton et al., 2005). In view that one advantage of the LHS method is that it can well represent the real distribution of variables using fewer simulation number (Schiozer et al., 2016), $N = 100$ is chosen to resample change factors of precipitation, minimum temperature and maximum temperature at station level in this study. This number is sufficient to explore the range of uncertainty in projected possible future climate scenarios without excessively large computational requirements, which has been indicated by Ledbetter et al. (2011) and Macdonald (2009). Through perturbing the historical observed daily climate series from 1971 to 2000 with the 100 sets of simulated change factors, the future climate series of 2041–2070 are obtained and can be further used to conduct the future hydrological simulations.

3.2. Hydrological model and hydrograph separation

The Hydrologiska Byråns Vattenbalansavdelning (HBV) model (Bergström and Forsman, 1973; Bergström and Lindström, 2015) is employed in this study because of its flexibility, computational efficiency and proven effectiveness under a wide range of climatic and

physiographic conditions (Beck et al., 2016; Finger et al., 2015; Li et al., 2015; Sun et al., 2017), including the mountain areas that are covered by glacier and snow (Hagg et al., 2007; Viviroli and Weingartner, 2004). The HBV model is a conceptual rainfall-runoff model and has been successfully applied in several regional studies (Booij, 2005; Lindström et al., 1997; Piotrowski et al., 2016). Four routines are incorporated in the model: (1) precipitation routine representing rainfall, snowpack and snowmelt; (2) evapotranspiration and soil moisture accounting routine; (3) fast runoff routine; and (4) slow runoff routine. The sum of fast runoff and slow runoff forms the total runoff. A detailed model structure and 13 model parameters can be found in Wawrzyniak et al. (2017). Input data are the elevation, minimum and maximum temperature, precipitation and potential evapotranspiration (PET) of meteorological stations.

In UYZR and ULR, the snowfall and snowmelt/glacier-melt processes are very important in the whole hydrological processes. Therefore, in this HBV model, a temperature index-based model (Lindström et al., 1997; Wawrzyniak et al., 2017) shown in Eq. (1) is adopted to simulate the division of rainfall and snowfall in this study. When the temperature is lower than the snowfall temperature threshold (here $TT - TTI/2$), precipitation all falls in the form of snow (i.e., snowfall). When the temperature is higher than the rainfall temperature threshold (here $TT + TTI/2$), precipitation is all in liquid phase (i.e., rainfall). If the temperature is between these two temperature thresholds, precipitation falls in the form of mixture of rainfall and snowfall. The snowmelt/glacier-melt process is simulated based on the degree-day factor model (Hinzman and Kane, 1991; Hock, 2003; Lindström et al., 1997). When the temperature is higher than the critical temperature TT , the glacier or snowpack begins to melt and the meltwater q_{sm} is calculated as Eq. (2). When the temperature decreases below the critical temperature TT , the meltwater starts to refreeze and the refreezing amount q_{sr} can be computed according to Eq. (3).

$$\begin{cases} P_s(t) = P(t), & P_r(t) = 0 \\ P_s(t) = P(t) * \frac{(TT + TTI)/2 - T}{TT}, & P_r(t) = P(t) * \frac{T - (TT - TTI)/2}{TT} \\ P_s(t) = 0, & P_r(t) = P(t) \end{cases} \quad \begin{cases} T(t) < TT - \frac{TTI}{2} \\ TT - \frac{TTI}{2} \leq T(t) < TT + \frac{TTI}{2} \\ T(t) \geq TT + \frac{TTI}{2} \end{cases} \quad (1)$$

$$q_{sm}(t) = \begin{cases} DDF \cdot (T(t) - TT) & T(t) > TT \\ 0 & T(t) \leq TT \end{cases} \quad (2)$$

$$q_{sr}(t) = \begin{cases} CFR \cdot DDF \cdot (TT - T(t)) & T(t) < TT \\ 0 & T(t) \geq TT \end{cases} \quad (3)$$

where t is the time in daily scale; P is the total precipitation with the liquid form P_r and the solid form P_s ; T is the daily average temperature;

Inducing correlation in change factors resampling based on the Cholesky decomposition

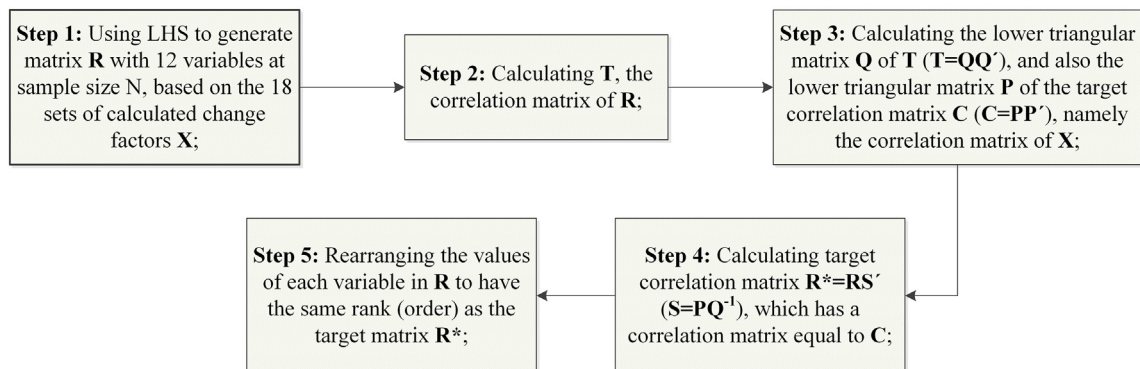


Fig. 3. Method of inducing the dependence structure in resampling change factors.

TT is the critical temperature when 50% of the precipitation occurs as rainfall and 50% as snowfall; TTI is the temperature span for mixture of rainfall and snowfall; DDF is the degree-day factor for glacier-melt or snowmelt ($\text{mm } ^\circ\text{C}^{-1} \text{ day}^{-1}$); and CFR is the refreezing factor of free water. The parameters of TT , TTI , DDF and CFR need to be calibrated.

According to the structure of the HBV model (Wawrzyniak et al., 2017), there are two types of runoff generated, i.e., fast runoff and slow runoff. Based on the input sources, the total runoff is finally divided into four components: rainfall-induced fast runoff (F_{rainfall}) and slow runoff (B_{rainfall}), and snowmelt-induced fast runoff (F_{snowmelt}) and slow runoff (B_{snowmelt}). In this study, we only focus on the annual runoff components, which can avoid the issue of delayed time for rainfall or snowmelt to transform into runoff at finer scale such as daily and monthly and it is relatively accurate to estimate annual runoff components (Weiler et al., 2018). Like Li et al. (2017), in this study snowmelt and rainfall are also assumed to have the identical infiltration rate in the whole hydrological system. In this way, the contribution of snowmelt and rainfall to fast runoff and slow runoff would be in proportion to their quantities. Therefore, the contribution percentages of the above four components to total runoff on annual scale can be respectively calculated as follows:

$$Q = F + B \quad (4)$$

$$F_{\text{rainfall}} = \frac{R}{R+S} \cdot F, f_{F,\text{rainfall}} = \frac{F_{\text{rainfall}}}{Q} \quad (5)$$

$$F_{\text{snowmelt}} = \frac{S}{R+S} \cdot F, f_{F,\text{snowmelt}} = \frac{F_{\text{snowmelt}}}{Q} \quad (6)$$

$$B_{\text{rainfall}} = \frac{R}{R+S} \cdot B, f_{B,\text{rainfall}} = \frac{B_{\text{rainfall}}}{Q} \quad (7)$$

$$B_{\text{snowmelt}} = \frac{S}{R+S} \cdot B, f_{B,\text{snowmelt}} = \frac{B_{\text{snowmelt}}}{Q} \quad (8)$$

in which Q is the total runoff (mm); F and B are respectively the fast runoff (mm) and slow runoff (mm) generated in the HBV model; R is the amount of rainfall (mm); S is the amount of snowmelt (mm); F_{rainfall} , B_{rainfall} , F_{snowmelt} and B_{snowmelt} are respectively the amount of rainfall-induced fast runoff and slow runoff and snowmelt-induced fast runoff and slow runoff, $f_{F,\text{rainfall}}$, $f_{B,\text{rainfall}}$, $f_{F,\text{snowmelt}}$ and $f_{B,\text{snowmelt}}$ are their corresponding ratios in the total runoff. Based on the above method, the four runoff components can be obtained.

3.3. Data preprocessing and model calibration

Considering the fact that there generally exists elevation-based increasing/lapse rate for precipitation and temperature, especially for high-elevation basins like the UYZR and ULR basins, the precipitation and temperature data in these two basins are respectively corrected according to their correction factor as Eq. (9) (Panagoulia, 1995) and Eq. (10) (Gao et al., 2012). Through investigating the relationship between observed temperature and elevation among meteorological stations in two basins, the temperature lapse rates are respectively found to be 0.58 and 0.90 ($^\circ\text{C}/100 \text{ m}$) in UYZR and ULR, which are within the range of the values (0–0.98 $^\circ\text{C}/100 \text{ m}$) found by Zhang et al. (2015). The precipitation lapse rates in UYZR and ULR are set to be

–6.0 mm/100 m, which is consistent with the findings by Cuo et al. (2013). After temperature correction, PET is calculated by the Hargreaves method (Hargreaves et al., 1985). The values of three parameters in the Hargreaves method, i.e., C , T and E , are respectively set to be 0.0014, 0.70 and 13.1 that are already calibrated by Hu et al. (2011) for China's southwest region.

$$\Delta P_i = \gamma_p (e_i - e_{c,i}) \frac{1}{100} \quad (9)$$

$$\Delta T_i = \gamma_T (e_i - e_{c,i}) \frac{1}{100} \quad (10)$$

where ΔP_i and ΔT_i are precipitation correction factor (mm) and temperature correction factor ($^\circ\text{C}$) for meteorological station i , respectively; e_i is the elevation (m) of meteorological station i ; $e_{c,i}$ is the average elevation (m) of the sub-basin that is controlled by meteorological station i ; γ_p represents the precipitation lapse rate (mm/100 m); and γ_T is the temperature lapse rate ($^\circ\text{C}/100 \text{ m}$).

The calibration of the HBV model is conducted using the generalized likelihood uncertainty estimation (GLUE) method (Beven, 2006; Tian et al., 2014), which emphasizes that there are behavior parameter sets having the same effects in simulating the hydrological processes and can be further used to analyze the uncertainty of model parameters. In total, 50,000 parameter sets are generated for model calibration and validation in both river basins. A comprehensive objection function Y (Akhtar et al., 2009) that combines the Nash-Sutcliffe coefficient of efficiency (NS) (Nash and Sutcliffe, 1970) and the relative volume error (RVE) is utilized to help better calibrate the model (Eqs. (11)–(13)). NS is commonly used to measure the agreement between the observed and simulated hydrographs with an optimal value of 1. RVE is included in the objective function to ensure that the modelled total runoff volume is similar to the observed total volume. In this study, the behavioral parameter sets are selected when the values of Y in the calibration and validation are both larger than 0.7 (Tian et al., 2014) and the RVEs are smaller than $\pm 20\%$ (James, 2003).

$$Y = \frac{NS}{1 + |RVE|} \quad (11)$$

$$NS = 1 - \frac{\sum_{i=1}^N [Q_m(i) - Q_o(i)]^2}{\sum_{i=1}^N [Q_o(i) - \bar{Q}_o]^2} \quad (12)$$

$$RVE = 100 \cdot \frac{\sum_{i=1}^N [Q_m(i) - Q_o(i)]}{\sum_{i=1}^N Q_o(i)} \quad (13)$$

where i is the time step, N is the total number of time steps, Q_m and Q_o are the modelled and observed runoff.

4. Results

4.1. Calibration and validation results of HBV model

According to the criterion that the evaluation indicator Y is larger than 0.7 and RVE is smaller than $\pm 20\%$ both in the calibration and validation period, 1460 sets of behavior parameters for the UYZR basin and 3769 sets for the ULR basin are obtained. Table 2 presents the values of

Table 2
Performance indices of HBV model in UYZR and ULR.

Basin	Number of behavior parameters	Calibration period			Validation period		
		Y	NS	RVE (%)	Y	NS	RVE (%)
UYZR	1460	0.70–0.80	0.70–0.81	–8.28–2.87	0.70–0.78	0.80–0.86	–18.69–9.23
ULR	3769	0.72–0.90	0.76–0.91	–5.25–15.19	0.72–0.87	0.79–0.91	–18.93–1.16

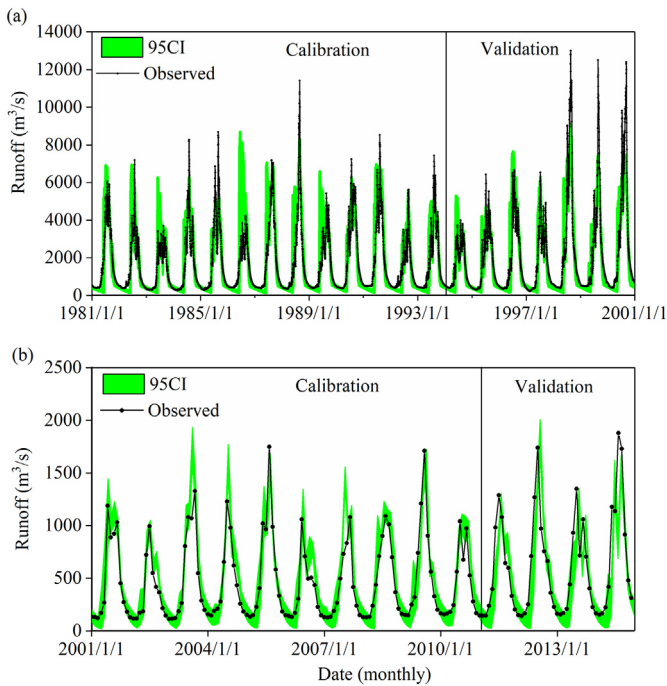


Fig. 4. Observed and simulated runoff in (a) UYZR and (b) ULR.

model performance indicators in these two river basins. On the whole, the HBV model is well calibrated and validated as indicated by high Y (0.70–0.90) and NS (0.70–0.91) and low RVE (–19%–16%) for both river basins. The median of Y , NS and RVE values in the calibration are respectively 0.72, 0.74 and –3.26% for the UYZR basin, and 0.75, 0.81 and 7.63% for the ULR basin. Compared with the calibrated results, the Y

values in the validation period for the two basins are not noticeably degraded although the simulated runoff volumes are to some extent underestimated, which are mainly caused by the existence of large peaks. The median values of Y , NS and RVE in the validation period are respectively 0.72, 0.83 and –14.87% in the UYZR basin and 0.74, 0.85 and –14.76% in the ULR basin. Since the evaluation of the ULR basin is conducted on monthly scale, its performance indicators are in general better than that of the UYZR basin and more behavior parameters are chosen. The observed runoff and 95% confidence interval (CI) of the simulated runoff is shown in Fig. 4. It can be seen that the seasonal patterns of runoff are all well captured while some peaks are underestimated in the UYZR basin, which have also been found by Zhang et al. (2013b). They claimed that the underestimation in streamflow simulation at Nuxia Station is highly likely to be caused by the largely underestimated CMA (i.e., China Meteorological Administration) observations in this area. Based on the above results, the selected behavior parameters in two basins are relatively satisfactory and can be further used to conduct the future hydrological simulation driven by the projected meteorological data from GCMs.

4.2. Generation of an ensemble of future change scenarios

Resampling 100 sets of change factor combinations for different meteorological variables, i.e., precipitation (P), maximum temperature (T_{max}) and minimum temperature (T_{min}), is conducted at each station in UYZR and ULR. Here, we use the results of one meteorological station, i.e., Nangqian Station that is located in the middle of the ULR basin, under RCP8.5, as an example to present the advantages of LHS method because the resampling results at all stations are similar although their projected change factors by GCMs may exist some differences. Fig. 5 shows the distribution of calculated change factors (18 sets) and resampled change factors (100 sets) and Fig. 6 presents the calculated and resampled dependence structures of change factors among 12 months at Nangqian Station. From Fig. 5, it can be seen

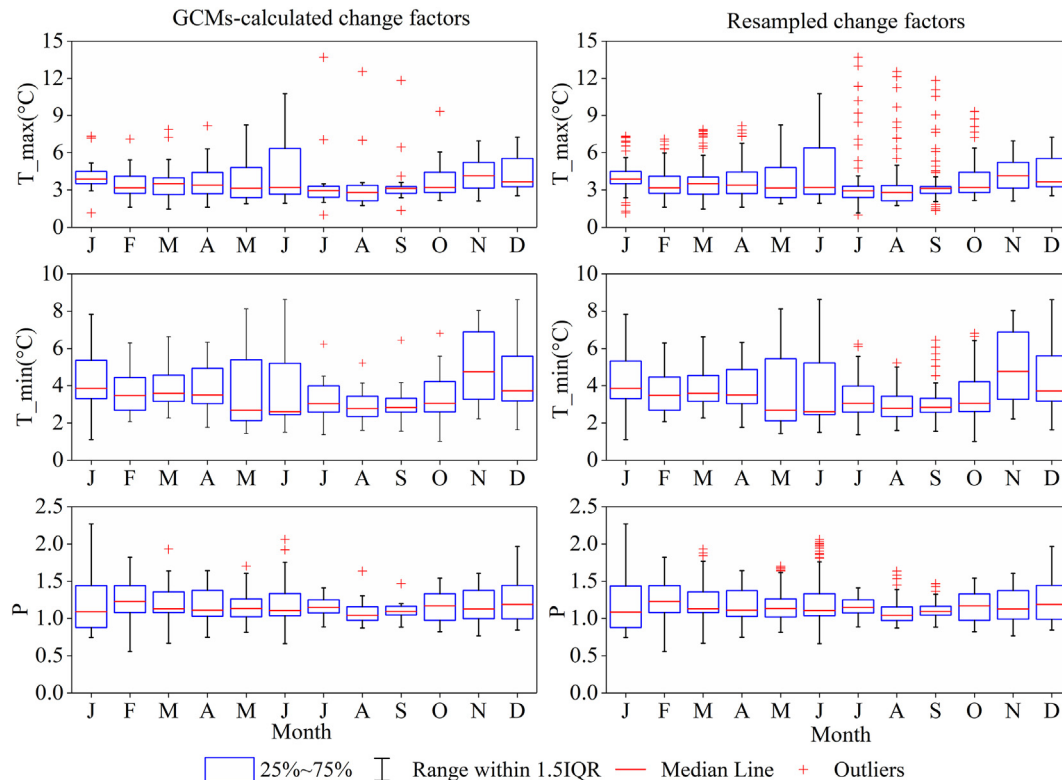


Fig. 5. Distribution of 18 sets of changes factors calculated from GCMs (left panel) and 100 sets of resampled change factors (right panel) for maximum temperature (top, T_{max}), minimum temperature (middle, T_{min}) and precipitation (bottom, P).

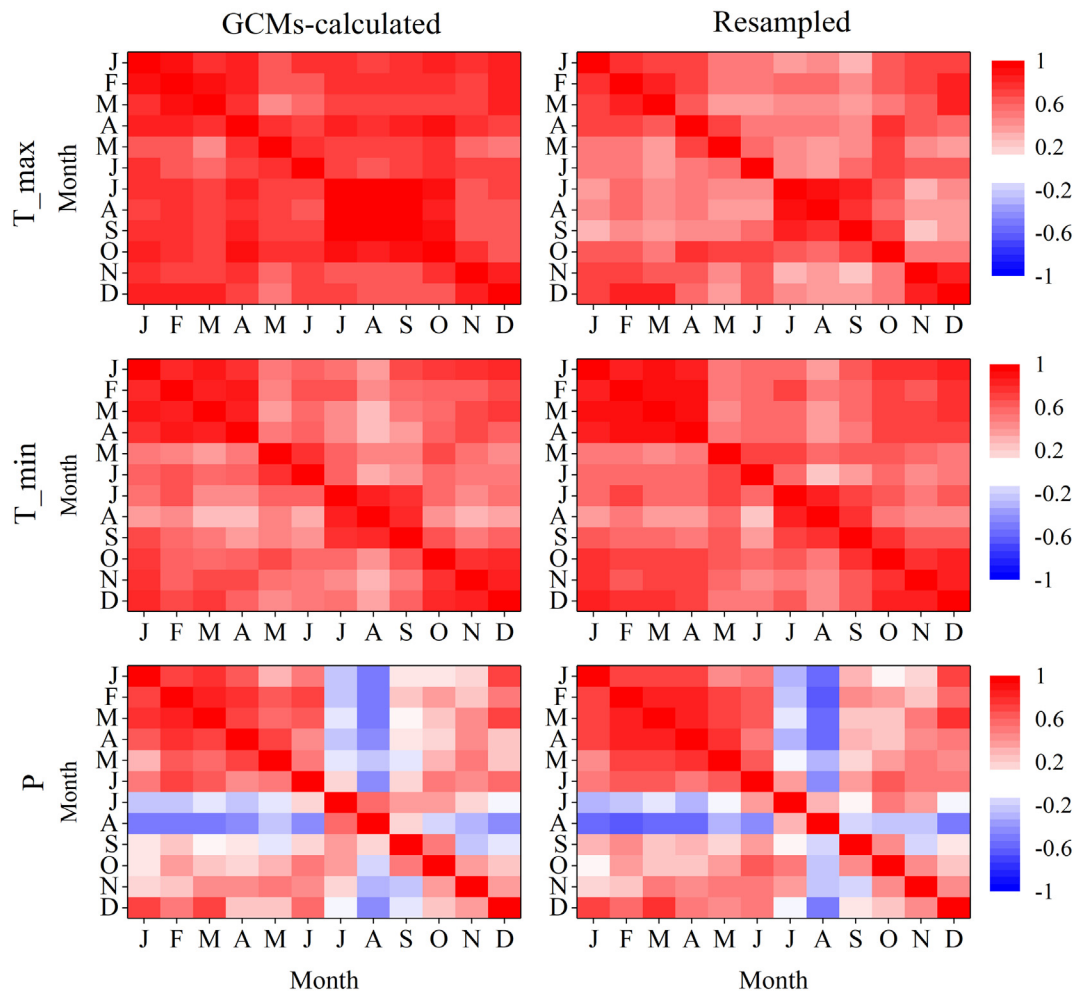


Fig. 6. Dependence structure of 18 sets of changes factors calculated from GCMs (left panel) and 100 sets of resampled change factors (right panel) for $T_{\max}$, $T_{\min}$ and P .

that in each month, the resampled change factors not only keep the probabilistic information of future change projected by different GCMs, but also generate new changes factors that have never occurred before, indicating that more multiple combinations of change factors can be formed to provide a wider set of possible future change scenarios, which is particularly evident for $T_{\max}$. To further check whether the resampling results of change factors are reliable, we use the two-sample Kolmogorov-Smirnov test to separately validate whether the calculated 18 sets of change factors and simulated 100 sets of change factors are from the same distribution for each month at the 5% significant level for $T_{\max}$, $T_{\min}$ and P . The results all demonstrate that the calculated and simulated change factors come from the same distribution. In Fig. 6, it is shown that the correlations of change factors of $T_{\max}$ between different months (0.5–1.0) are the highest, followed by that of $T_{\min}$ (0.3–0.9) and P (–0.5–0.8). Therefore, the dependence of changes factors cannot be neglected in the resampling process. In addition, no matter what the dependence structures of $T_{\max}$, $T_{\min}$ and P are, they are all well maintained in spite of slight underestimation for $T_{\max}$ (Fig. 6). In summary, the LHS method considering inherent dependence structures of variables is an effective approach to generate a wider ensemble of future change scenarios to fully reflect the uncertainty of GCM projections.

4.3. Projections of meteorological variables

After perturbing the observation-based climate forcing data with the 100 sets of change factors of P , $T_{\max}$ and $T_{\min}$ at each meteorological station in UYZR and ULR, climate forcing data in the future period under

RCP2.6 and RCP8.5 are obtained. Fig. 7 demonstrates the projected basin-averaged precipitation (P), mean temperature (T) and potential evapotranspiration (PET) and corresponding percentage changes in the future period 2041–2070 with respect to the baseline period 1971–2000. Projected precipitation varies among seasons and basins. For the UYZR basin, precipitation is all projected to increase for the monsoon season (May–Sep) with the median increase about 10% under RCP2.6 and approximately 17.5% under RCP8.5, and the uncertainties in the monsoon season are smaller than that in the dry season (Nov–Mar). The uncertainty hereafter refers to the 95% confidence interval. In the dry season, the uncertainty in the future precipitation projections is very large with the median close to 0%, implying that the change trend of precipitation is highly uncertain or maybe there is no trend at all. Compared with the UYZR basin, there is no apparent seasonality in precipitation changes in the ULR basin. In this basin, the medians of the projected change in precipitation throughout the year all indicate an increasing trend with rising about 10% under RCP2.6 and 16% under RCP8.5. Moreover, the projected changes of precipitation above the median in different months in ULR all present a larger range, demonstrating that precipitation would be more likely to grow in the future. At the annual scale, the UYZR basin exhibits a moderate increase (4.0–16.5%) in the precipitation with the median of 9.5% under RCP2.6 and 9.6–23.0% of increase under RCP8.5 with the median of 15.3%. Similarly, moderate changes also occur in the annual precipitation of the ULR basin with the median of 9.0% (–5.7–21.2%) and 14.3% (3.3–35.6%) respectively for RCP2.6 and RCP8.5. In both basins, the uncertainty of the projected change in precipitation under RCP8.5 is always larger than that under RCP2.6.

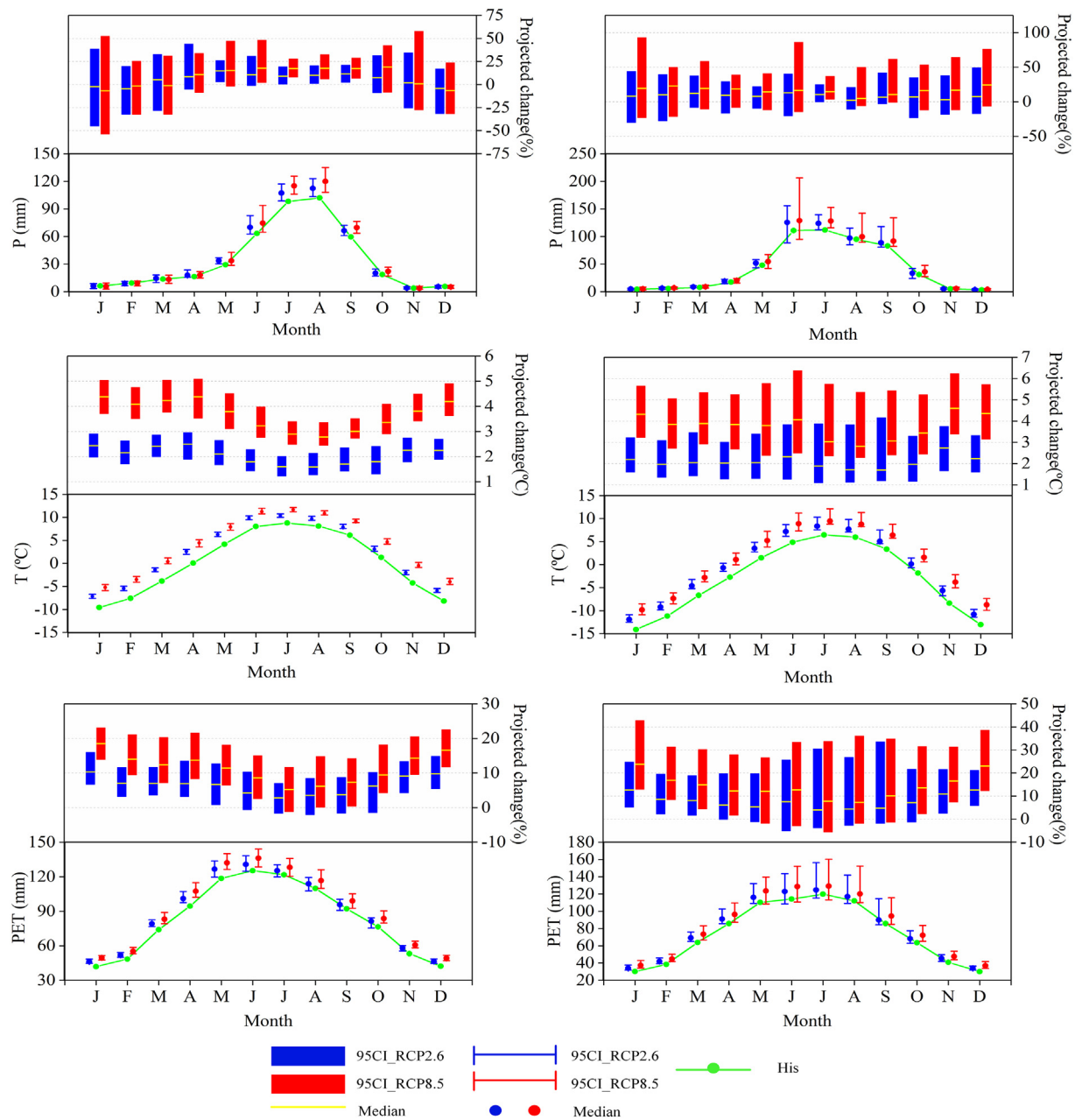


Fig. 7. Projections and projected change of areal mean P (top), T (median) and PET (bottom) in the future period 2041–2070 with respect to the baseline period 1971–2000 under RCP2.6 and RCP8.5, respectively in the UYZR basin (Left panel) and ULR basin (Right panel). The historical meteorological data are indicated in green color, and the projected climate condition under RCP2.6 and RCP8.5 are respectively in blue color and red color. The uncertainty of GCMs projections and projected change are respectively reflected in the interval plot and boxplot, in which the central dot/line is the median, and the edges of the interval plot/boxplot are the 2.5th and 97.5th percentiles.

Temperature is projected to increase for all seasons with the largest warming appearing in winter and spring and the smallest warming in summer for the two basins, which is consistent with the findings by Su et al. (2016). In the UYZR basin, the projected temperature increase is <3 °C and the uncertainty is within 1.0 °C under RCP2.6. Under RCP8.5, a remarkably greater warming (2.5–5.0 °C) and larger uncertainty amplitude (about 1.5 °C) are observed. Compared with the temperature change in the UYZR basin, the differences in the ULR basin are that the uncertainty becomes much larger (1.5–3.9 °C) and the largest uncertainty occurs in summer for both RCP2.6 and RCP8.5. Annual mean temperature is projected to increase by 1.7–2.3 °C and 3.3–4.1 °C, respectively, under RCP2.6 and RCP8.5 in the UYZR basin, and by 1.5–3.3 °C and 2.8–5.5 °C, respectively, under RCP2.6 and RCP8.5 in the ULR basin. Since PET is mainly dominated by

temperature, its seasonal projected change pattern is similar to that of temperature. In the UYZR basin, annual mean PET is projected to increase by 2.9–9.3% with the median of 5.9% under RCP2.6 and by 6.6–14.5% with the median of 10.3% under RCP8.5. In the ULR basin, annual mean PET is projected to increase by 0.6–21.1% (the median is 6.8%) and 3.2–26.7% (the median is 12.3%) under RCP2.6 and RCP8.5 respectively. Fig. 7 shows that more precipitation, greater warming and more potential evapotranspiration would generally appear in the future period, and the change extent under RCP8.5 is larger than that under RCP2.6. In addition, the uncertainty ranges of meteorological variables' projected change in ULR are larger than that in UYZR, which are to large extent associated with GCMs' different performance features in the Indian monsoon region and the Asian monsoon region.

4.4. Projected change of runoff

In this section, with 1460 sets of behavior parameters in the UYZR basin, 1460 sets of runoff simulations driven by the historical forcing data for the baseline period (1971–2000) and 146,000 sets of runoff simulations driven by 100 sets of projected forcing data for the future period (2041–2070) are respectively obtained using the HBV model, and then the 95% confidence interval (95CI) of mean monthly and annual runoff are computed to analyze their projected change. Similarly, 3769 sets of runoff simulations for the baseline period and 376,900 sets of runoff simulations for the future period are respectively conducted in the ULR basin. Fig. 8 shows monthly total runoff and their projected changes in the median in the UYZR basin. In the baseline period, the total runoff pattern is similar to that of precipitation (Fig. 7) and peaks mainly occur in July and August. Compared with the baseline period, a slightly different pattern in the projected total runoff under both scenarios is observed, in which the total runoff presents an obviously large increase in April and May and a decrease in June and July, and peak flows shift from July and August to August and September. This is mainly because snowmelt peak shifts to earlier spring with the warming climate, causing snowmelt runoff dramatically growing up in April and in May and a considerable decrease in the snowmelt runoff in June and July. Meanwhile, compared to the other months, the largest increase in precipitation and the least increase in evapotranspiration (see Fig. 7) in August and September would contribute to a more remarkable increase of runoff in these two months. Furthermore, the runoffs are projected to increase for months from August to May of the following year, which is mainly related to increased precipitation. Under RCP8.5, more obvious change trend of total runoff is observed than that under RCP2.6.

As for the fast runoff and slow runoff in the UYZR basin, their seasonal changes under RCP2.6 and RCP8.5 are shown in Fig. 9. The

seasonal change trend of fast runoff is similar to that of the total runoff and the causing reasons are also the same. Slow runoff is relatively stable and shows slight growth throughout the year due to increased precipitation in the future under RCP2.6 (0.5–1.9 mm for the median) and under RCP8.5 (0.8–3.1 mm for the median). To further obtain the contribution of rainfall- and snowmelt-induced fast runoff and slow runoff to the total runoff, we analyzed their amounts (Fig. 10(a)) and their contributions to the total runoff (Fig. 10(b)) at the annual scale in the UYZR basin under different scenarios. In the future period, due to the increased precipitation, the total runoff exhibits an ongoing trend with the median increased by 6.2% under RCP2.6 and 9.4% under RCP8.5. Rainfall-induced fast runoff ($F_{rainfall}$) and slow runoff ($B_{rainfall}$) are also projected to increase under both scenarios. However, with less snow falling in the future, snowmelt-induced runoff experiences a downward trend, and the contribution of snowmelt-induced fast runoff ($F_{snowmelt}$) and slow runoff ($B_{snowmelt}$) to the total runoff has also declined. In the baseline period, $F_{rainfall}$ contributes 48.8–57.5% to the total runoff and is the biggest contributor, $B_{rainfall}$ contributes the second accounting for about 16.5–23.7% and the contributions of $F_{snowmelt}$ and $B_{snowmelt}$ are small, respectively making up 16.9–22.7% and 5.8–9.0%. Under RCP2.6, the median of $F_{rainfall}$ and $B_{rainfall}$ in the future are projected to increase by 3.8% and 4.9% respectively, and that of $F_{snowmelt}$ and $B_{snowmelt}$ decreases by 6.7% and 1.9% respectively. Under RCP8.5, the change amplitudes of the four runoff components are further enhanced, with the increase percentage reaching 5.2% for $F_{rainfall}$ and 8.0% for $B_{rainfall}$, and the decrease of $F_{snowmelt}$ and $B_{snowmelt}$ reaching 10.1% and 3.1%, respectively.

In the ULR basin, monthly total runoff and its projected change are shown in Fig. 11. Fig. 12 presents the monthly change of fast runoff and slow runoff. From Figs. 11 and 12, it can be seen that for the ULR basin, the future total runoff and its fast and slow runoff present similar change patterns with that of the UYZR basin, and the reasons that

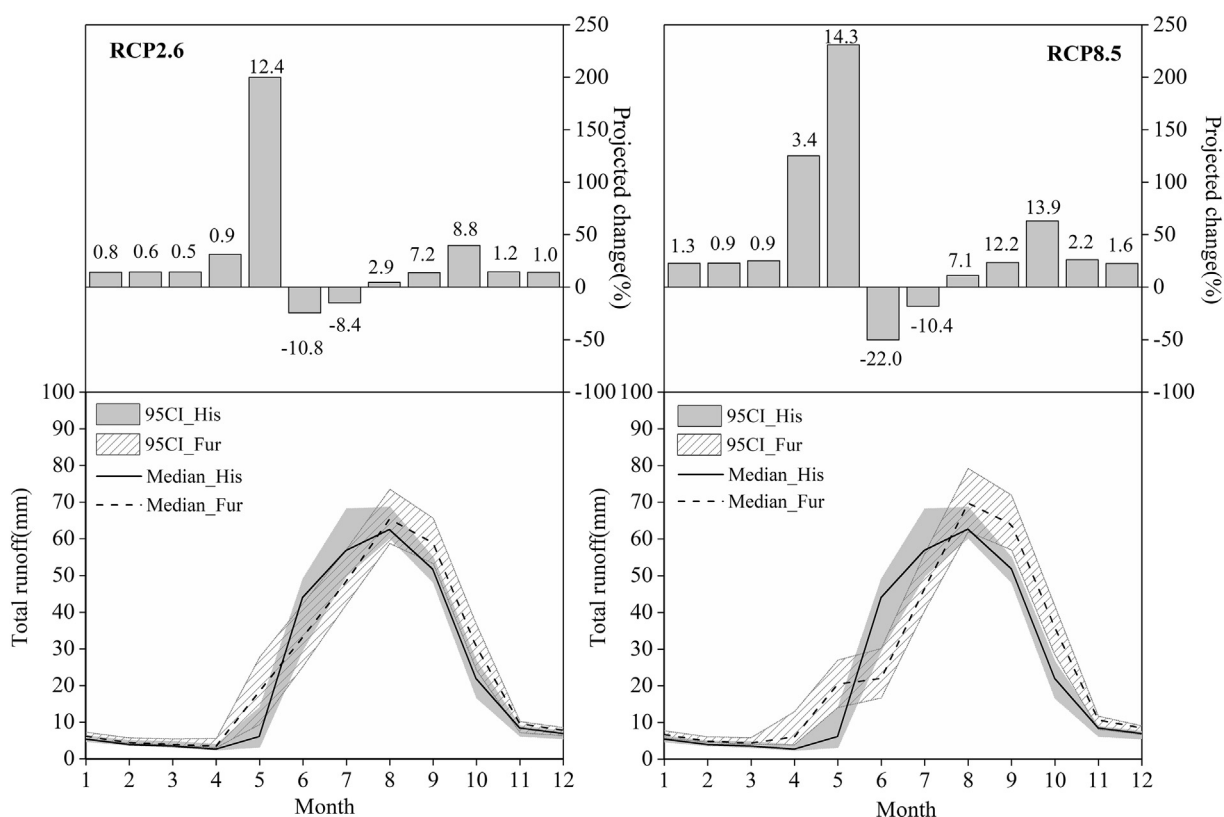


Fig. 8. Mean monthly runoff for the baseline period 1971–2000 and projections for the future period 2041–2070 (bottom panel), and projected runoff median change (top panel) under RCP2.6 (left panel) and RCP8.5 (right panel) for the UYZR basin. In the top panel, the bars indicate the projected relative change of runoff and the numbers above the bars represent the absolute change amount.

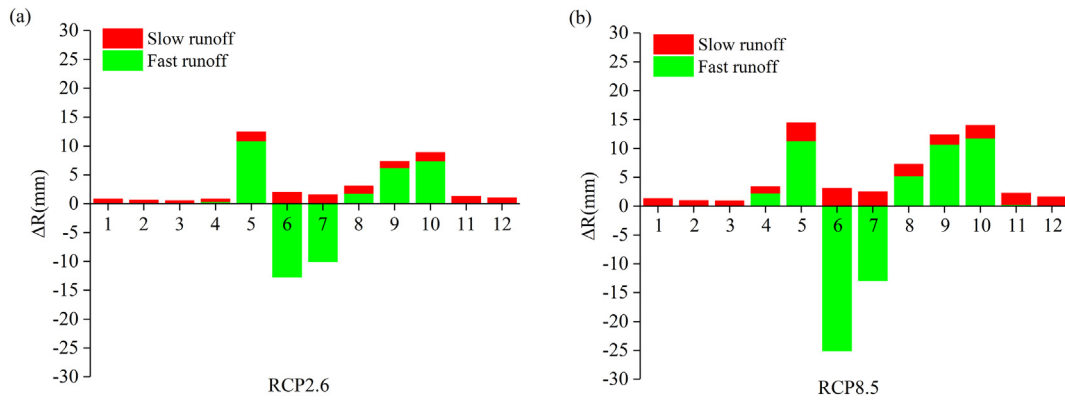


Fig. 9. Monthly changes in the median of fast runoff and slow runoff during the future period 2041–2070 relative to the baseline period 1971–2000 under (a) RCP2.6 and (b) RCP8.5 for the UYZR basin.

caused these changes explained in the UYZR basin can also be transplanted to this area to large extent. Nevertheless, differences still exist between the ULR and UYZR basins. Compared with the UYZR basin, one clear difference in the ULR basin is that the uncertainty of the projected runoff in the monsoon-dominated months (i.e., June to September) under RCP8.5 is much larger than that under RCP2.6, which is closely associated with the uncertainty range of ULR's future precipitation changes under the two scenarios (see Fig. 7). In the ULR basin, the uncertainty of the projected precipitation change in June–September under RCP8.5 is much larger than that under RCP2.6, especially for June. The uncertainty of precipitation and runoff is larger in ULR than that in UYZR. Another observed difference in ULR is that positive total runoff and fast runoff changes occur in June and July, which is contrary to that of UYZR. This is because snowcover has almost all melt in April and May and there is little snowmelt left in June and July in ULR, so all increased precipitation falls in the form of rainfall resulting in increase of total runoff and fast runoff. In addition, the decrease of total runoff and fast runoff in April and May and substantial increase in March in ULR are mainly due to earlier snowmelt under RCP2.6 and RCP8.5. At the annual scale shown in Fig. 13, the total runoff in ULR grows up by 9.6% under RCP2.6 and by 15.4% under RCP8.5. Furthermore, like in the UYZR basin, the snowmelt time advances about one month under RCP2.6 and around 1–1.5 months under RCP8.5. The

reduced snowmelt-induced runoff (i.e., F_{snowmelt} and B_{snowmelt}) and increased rainfall-induced runoff (i.e., F_{rainfall} and B_{rainfall}) are also found in the ULR basin, and their change amplitudes under RCP8.5 are larger than that under RCP2.6. Since there is very limited snow covered in this area, the contribution of snowmelt-induced runoff only accounts for 12.3–22.5% in the baseline period and would become less in the future, i.e., 7.0–14.5% under RCP2.6 and 5.1–10.9% under RCP8.5. In ULR, the fast runoff and slow runoff have almost equivalent contributions, respectively making up 44.6–58.4% and 41.6–55.4% of the total runoff in the baseline period. In the long term, their median would be projected to increase by 1.2% and –1.2% for RCP2.6, and 2.1% and –2.1% for RCP8.5. Although the amount of slow runoff rises in the future (see Fig. 12), its proportion may decrease, indicating that fast runoff and rainfall-induced runoff would become more important in this area.

5. Discussion

In this study, the impacts of climate change on the total runoff and runoff components in the UYZR and ULR basins were investigated in detail, which is very essential to help better understand the responses of hydrological processes in these high mountain regions. The results show that there are possibly more precipitation and total runoff in both river basins, which are consistent with the results reported by

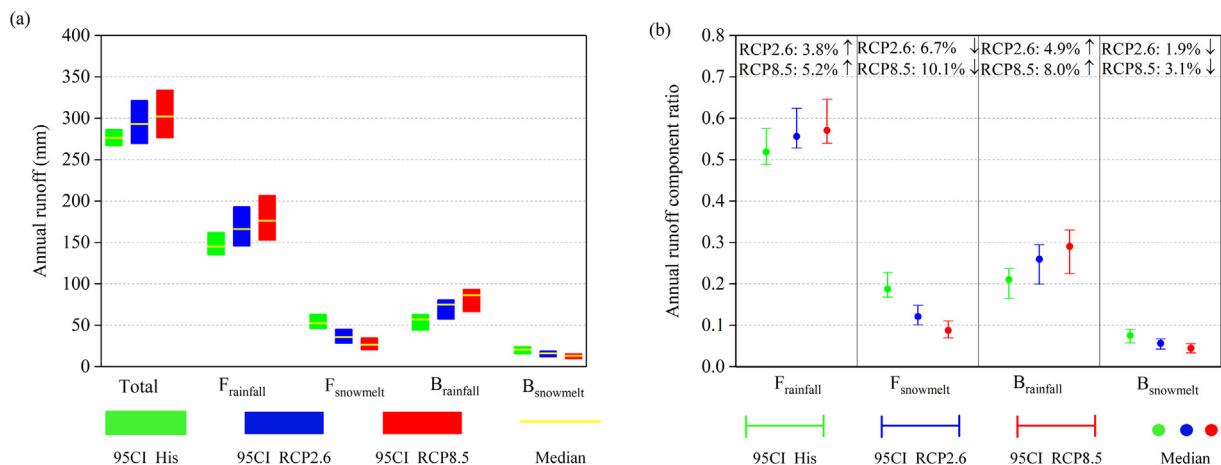


Fig. 10. (a) Mean annual total runoff, rainfall-induced fast runoff (F_{rainfall}) and slow runoff (B_{rainfall}) and snowmelt-induced fast runoff (F_{snowmelt}) and slow runoff (B_{snowmelt}), and (b) corresponding contribution of the four runoff components to total runoff in the baseline period 1971–2000 and the future period 2041–2070 under RCP2.6 and RCP8.5 in UYZR. Green color indicates the historical situation, and blue and red colors respectively indicate the future projections under RCP2.6 and RCP8.5. In the boxplot and interval plot, the edges are the 2.5th and 97.5th percentiles and the yellow line in the middle is the median.

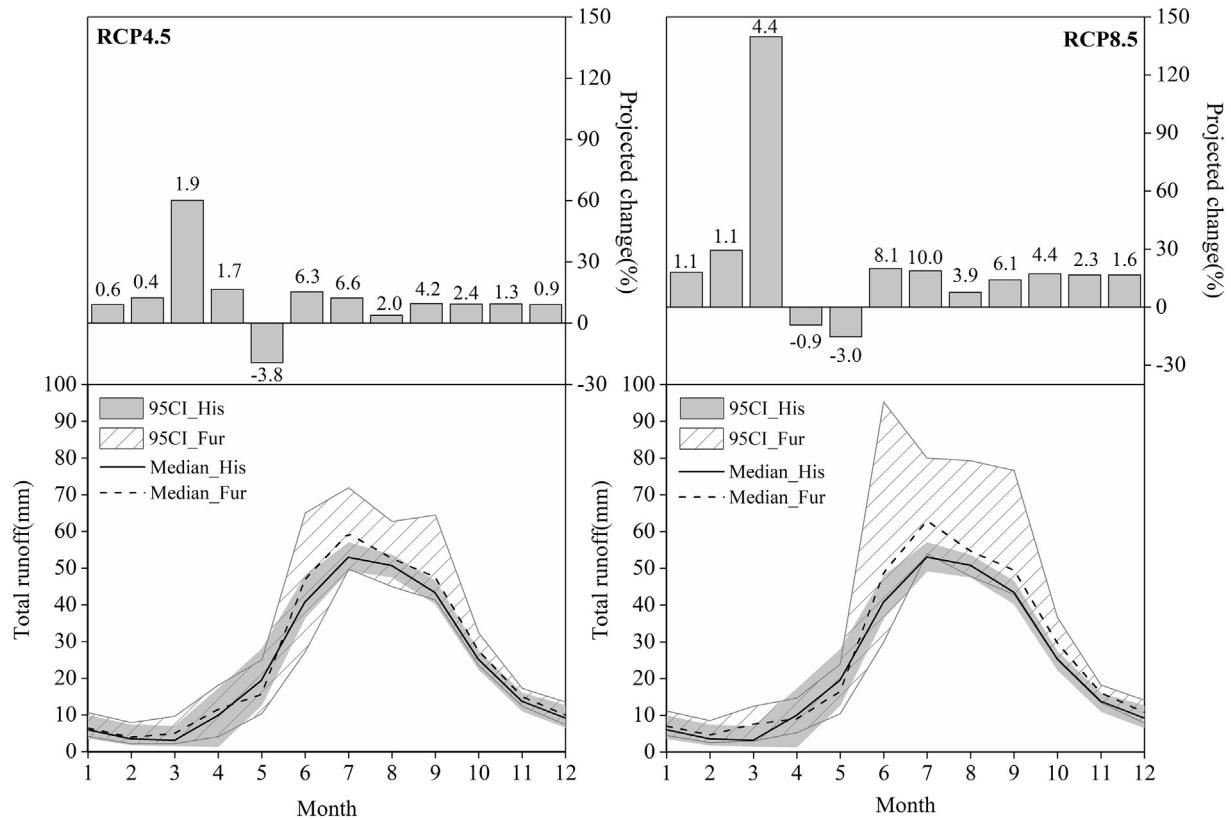


Fig. 11. Mean monthly runoff for the baseline period 1971–2000 and projections for the future period 2041–2070 (bottom panel), and projected runoff median change (top panel) under RCP2.6 (left panel) and RCP8.5 (right panel) for the ULR basin. In the top panel, the bars indicate the projected relative change of runoff and the numbers above the bars represent the absolute change amount.

many previous studies (Hoang et al., 2016; Immerzeel et al., 2013; Li et al., 2013b; Lutz et al., 2014; Su et al., 2016). The projected increase tendency of total runoff here indicates that there would possibly be more water available in the future that can be used for social and economic development in these areas and their downstream reaches. Furthermore, the increased slow runoff throughout the year will provide sustainable security for ecological water in the rivers. The distributed pattern of slow runoff within the year is in line with the findings by Lutz et al. (2014) and Singh and Jain (2003) with relatively high slow runoff occurring in the second half of the year that is mainly due to the delayed infiltration of fast runoff peaks in the monsoon-dominated seasons. With knowledge of the change pattern of total runoff and each

runoff component at the monthly scale, it would be helpful to design effective measures to cope with extreme events, like frequent flood and droughts in these basins.

As for the uncertainty existing in climate change assessment, we mainly considered two large uncertainty sources, i.e., GCMs and hydrological model parameters in this study. The uncertainty of runoff in the baseline period is caused by model parameters, while the uncertainty of runoff in the future period is the joint results of GCMs and model parameters. From the runoff uncertainty in the UYZR basin shown in Fig. 8, it is hard to tell the extent to which these two uncertainty sources contribute to future extreme runoff uncertainty. While in the ULR basin, it can be seen from Fig. 11 that the uncertainty of total runoff in the future

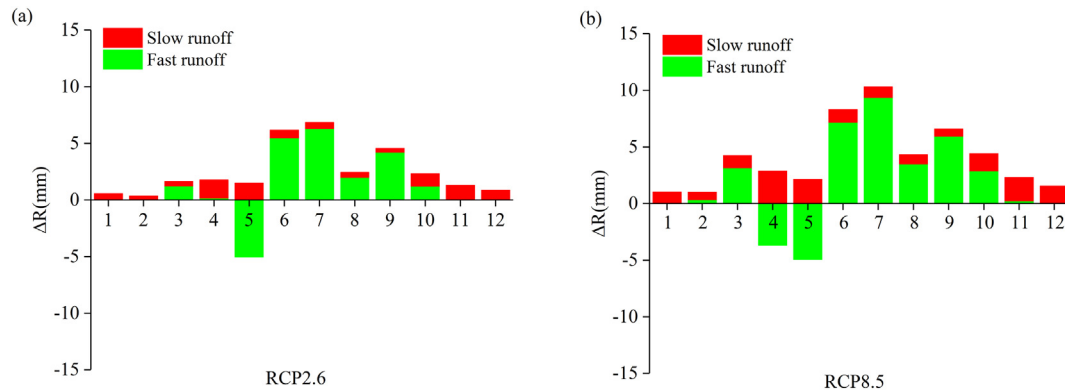


Fig. 12. Monthly changes in the median of fast runoff and slow runoff during the future period 2041–2070 relative to the baseline period 1971–2000 under (a) RCP2.6 and (b) RCP8.5 for the ULR basin.

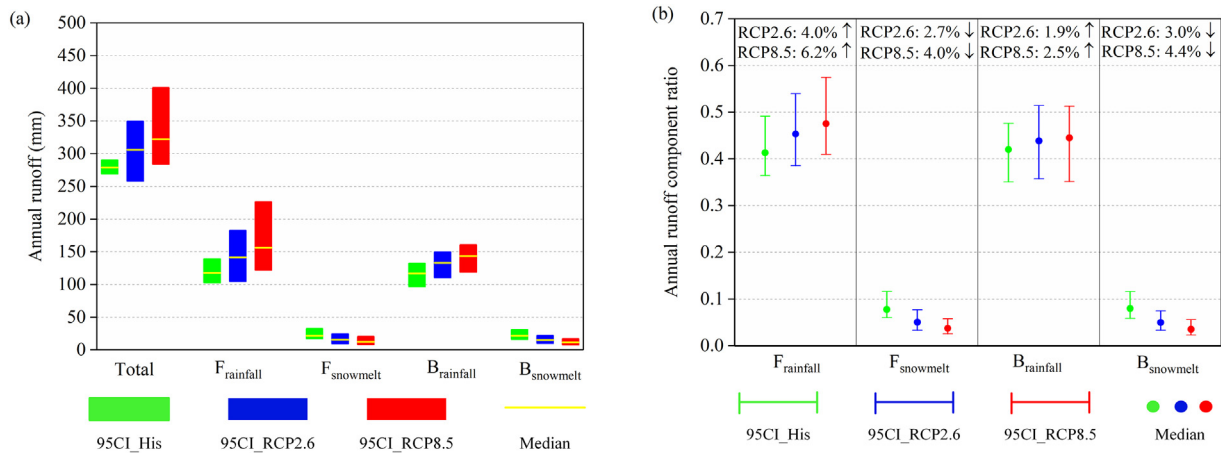


Fig. 13. (a) Mean annual total runoff, rainfall-induced fast runoff ($F_{rainfall}$) and slow runoff ($B_{rainfall}$) and snowmelt-induced fast runoff ($F_{snowmelt}$) and slow runoff ($B_{snowmelt}$), and (b) corresponding contribution of the four runoff components to total runoff in the baseline period 1971–2000 and the future period 2041–2070 under RCP2.6 and RCP8.5 in ULR. Green color indicates the historical situation, and blue and red colors respectively indicate the future projections under RCP2.6 and RCP8.5. In the boxplot and interval plot, the edges are the 2.5th and 97.5th percentiles and the yellow line in the middle is the median.

period is much larger than that in the baseline, particularly for the monsoon-dominated seasons, which means GCMs contribute larger uncertainty in this basin. In addition, the runoff uncertainty under RCP8.5 is much larger than that under RCP2.6. From Fig. 14, it can be seen that the uncertainty of precipitation projected by GCMs under these two scenarios is the direct reason for this, which further illustrate GCMs is the dominant uncertainty source in the future runoff in ULR. Nevertheless, there are other uncertainty sources like future emission scenarios, downscaling methods and hydrological model structures that are not considered in this study. Only two emission scenarios, one hydrological model and one downscaling method were used, which may underestimate the uncertainty of the final runoff outputs to some extent. Numerous studies have investigated the impacts of different uncertainty sources in climate change impact analysis and could give us some useful insights (Kay et al., 2008; Vetter et al., 2016; Zhang et al., 2014). Vetter et al. (2016) found that GCMs is the largest uncertainty source, followed by RCPs and the smallest is hydrological models. However, Tian et al. (2016) found that the order of uncertainty sources of high flows from high to low is: hydrological models, GCMs, parameters and emission scenarios, in Jinhua basin, China. Different study cases may have different conclusions. To assess the uncertainty of runoff and runoff components more systematically, a more complete framework of uncertainty in this region are expected to be built.

Although many studies have attempted to quantify the contribution of different runoff components including rainfall, snowmelt, and glacier melt at daily or monthly time scales, it is still a challenging task. On the one hand, the input sources always need response time to form runoff in the hydrologic system (Weiler et al., 2018). On the other hand, the mixing of rainfall and melt water in soil and groundwater stores is rather complicated and their contribution to runoff may not only delay, but also vary with time due to the related evapotranspiration process and changed discharge dynamics (Panday et al., 2014), which is difficult to observe, measure or parameterize in the model (Weber et al., 2010). These all make it very difficult to accurately quantify the contribution of rainfall and melt water at finer scale (Weiler et al., 2018). Therefore, in this study we only focus on quantification of the long-term (annual) average contribution of different runoff components. From the results shown in Table 3, it can be seen that the hydrological regimes are different in the UYZR and the ULR basins. From the point of view of runoff generation process, fast runoff is the dominant contributor in the UYZR basin, while in ULR slow runoff plays the same role as fast runoff. In the future period, the function of slow runoff will strengthen in the UYZR basin but diminish in the ULR basin. From the point of view of the input sources, more snowpack or glacier are covered in UYZR than in ULR, which result in larger contribution of snowmelt runoff in the UYZR basin. Rainfall-induced runoff is dominated in both

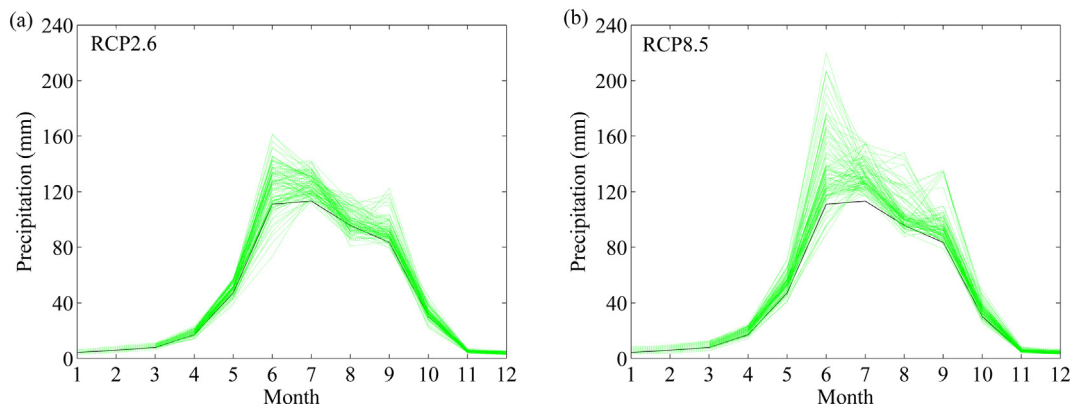


Fig. 14. All rainfall projections under RCP2.6 and RCP8.5 in the ULR basin. Black lines represent the historical results and green lines represent the future results.

Table 3

Contribution of different runoff components to total runoff in the baseline period and corresponding median change in the future period under RCP2.6 and RCP8.5 in the UYZR and ULR basins.

Basin	Fast runoff $F_{\text{rainfall}} + F_{\text{snowmelt}}$			Slow runoff $B_{\text{rainfall}} + B_{\text{snowmelt}}$			Rainfall-induced runoff $F_{\text{rainfall}} + B_{\text{rainfall}}$			Snowmelt-induced runoff $F_{\text{snowmelt}} + B_{\text{snowmelt}}$		
	His	RCP2.6	RCP8.5	His	RCP2.6	RCP8.5	His	RCP2.6	RCP8.5	His	RCP2.6	RCP8.5
UYZR	69.1–78.4%	–2.8%	–4.7%	21.6–30.9%	2.8%	4.7%	68.6–75.9%	8.6%	13.1%	24.1–31.4%	–8.6%	–13.1%
ULR	44.6–58.4%	1.2%	2.1%	41.6–55.4%	–1.2%	–2.1%	77.5–87.7%	5.5%	8.2%	12.3–22.5%	–5.5%	–8.2%

basins, which is consistent with the results by Guan and Chen (1980) in the ULR basin, Liu (1999) in the UYZR basin and other studies in TP (Lutz et al., 2014; Su et al., 2016). With temperature increasing, rainfall-induced runoff is expected to become more important while the role of snowmelt-induced runoff decreases in the long run, which keeps in line with the findings by Lutz et al. (2014).

6. Conclusions

In this study, a general framework was proposed to better investigate the responses of hydrological processes to climate change in the UYZR and ULR basins. Firstly, to fully consider the uncertainty of GCMs projections, the LHS method considering the inherent dependence structures of variables was introduced to provide a broader ensemble of climate projections by resampling changes factors of precipitation, minimum and maximum temperature from 18 GCMs. Secondly, the HBV model was calibrated and validated against daily streamflow data in the UYZR basin and monthly streamflow data in the ULR basin, and the final selected behavior parameter sets ($Y > 0.7$ and RVE within $\pm 20\%$ both in calibration and validation) were utilized to conduct the hydrological modelling in these two basins. Lastly, the projected changes of total runoff and four runoff components, i.e., fast runoff and slow runoff respectively induced by rainfall and snowmelt, in the future period 2041–2070 relative to the baseline period 1971–2000, were determined through model simulations. The main results are summarized as follows:

- (1) The LHS method can generate an ensemble of change factors for different meteorological variables while simultaneously well maintain the dependence structure inherent of change factors for each meteorological variable, reflecting fully the uncertainty of GCM projections and climate stochasticity.
- (2) In the UYZR and ULR basins, annual precipitation P , mean temperature T and potential evapotranspiration PET at the basin level are projected to increase with the warming climate. In the UYZR (ULR) basin, the median of P , T and PET will increase by 9.5% (9.0%), 2.1 °C (2.1 °C) and 5.9% (6.8%) under RCP2.6, and 15.3% (14.3%), 3.7 °C (3.8 °C) and 10.3% (12.3%) under RCP8.5 respectively. In addition, the uncertainty ranges of projected change of meteorological variables in the ULR basin are all larger than that of the UYZR basin.
- (3) In both basins, the total runoff presents an upward trend with increase of 6.2% under RCP2.6 and increase of 9.4% under RCP8.5 in UYZR, and with increase of 9.6% and 15.4% respectively under two scenarios in ULR. The dominant causes for the increasing total runoff in these two basins are both due to the increasing precipitation in the future period. In addition, with warming climate, earlier snowmelt in spring can be observed in both basins, and the amount of snowmelt-induced runoff decreases as more precipitation would fall in the form of rain and less in the form of snow. The snowmelt peak time will advance approximately 1–1.5 months under RCP2.6 and RCP8.5. Furthermore, slow runoff exhibits moderate increase throughout the year under both scenarios in both basins.
- (4) The hydrological regimes are different in the UYZR and ULR basins. In UYZR, fast runoff contributes about 69.1–78.4% to the

total runoff and slow runoff contributes only about 21.6–30.1%, while in ULR the contributions of fast runoff and slow runoff to the total runoff are almost the same, contributing about 44.6–58.4% and 41.6–55.4% respectively. In addition, the contribution of snowmelt-induced runoff in the ULR basin (12.3–22.5%) is smaller than that in the UYZR basin (24.1–31.5%) because there is limited snow within ULR. In the future, the snowmelt water would exert less impacts on the total runoff and rainfall-induced runoff would become more important, especially under RCP8.5.

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